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Automatic recognition of anuran species based on syllable identification

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A B S T R A C T

Monitoring of biological populations is well known for being a complex task that involves high operational costs, unknown reproductive intervals of the studied species, and difficult visualization of isolated individuals (due to their mimetic and cryptic capabilities). Therefore, the development of new methodologies able to measure quantities of individuals in specific biological populations without direct contact is desired. Species and individual recognition, based on acoustic analysis of their calls (Bioacoustics), is possible for many animals and has proven to be a useful tool in the study and monitoring of animal species. In this paper, an unsupervised methodology for anuran automatic identification is proposed; it is based on the use of a fuzzy classifier and Mel Frequency Cepstral Coefficients. This methodology is able to detect species not presented in the training stage, although they belong to different populations. Additionally, correlations among species of the same genus can be determined through the similarities of their calls. For testing the proposed method, two different datasets with species from the north-eastern Colombia (Chocó and Antioquia departments with 103 and 813 mating calls respectively) were used. In validation tests performed, accuracies between 99.38% and 100% were achieved in all species by applying the proposed methodology to both datasets. Thirteen different species of anurans in both datasets were correctly identified.

1. Introduction

Amphibians—especially anurans—have been suffering reductions in their distribution (Whittaker et al., 2013). Recent studies about the origins of this reduction in specific locations revealed that regional warming, UV radiation increase, and epidemic diseases could be partially induced by the growth of human impact in climatic and ecological systems (McCallum, 2007). Unfortunately, nowadays a detailed analysis to determine the source of the global anuran population decrease is almost non-existent (La Marca et al., 2005). These declines cannot be disentangled from natural temporal fluctuations, and merely a long term dataset would provide the necessary statistical significance to conclude whether a population is stable in a particular time epoch (La Marca et al., 2005). This evidences the necessity of going beyond the established archetypes of biological population surveys, by developing new methodologies with the purpose of comprehending and suggesting solutions for the phenomenon of amphibian declines.

Identification of animals based on acoustic parameters is known for being a noninvasive methodology for recognizing individuals of the same species. It has considerable advantages (less time consuming, less cost, and harmless to habitat) over typical marking procedures as toe clipping, attached devices, passive transponders, or chemical-like branding (Beausoleil et al., 2004). Manual analysis of the acoustic data by experienced surveyors can produce accurate results; however, the time and effort required to process even small volumes of data can make manual analysis prohibitive (Wimmer et al., 2013). Therefore, automatic methodologies able to perform detection and identification of species in recordings are required.

An effective acoustic recognition technique must extract discriminating features which maximize between-group (inter-specie) dissimilarity and minimize within-group (intra-specie) dissimilarity, and then use them as input to a classifier (Cheng et al., 2010). A good classifier should determine when a feature vector does not belong to any of the known groups. Conventionally, statistical multivariate methods are used for this task; however, most of them are limited to linear models and have low flexibility interpreting ecological data (Park and Chon, 2007). Nowadays, the use of artificial intelligence methodologies in applications related with biology and medicine is increasing (Hassanien et al., 2013). Their capability of reducing the human interaction minimizes the time consumption in data analysis, allows researchers to work with large amounts of data, and increases the probabilities of reaching the expected results. Therefore, techniques able to use any type of information extracted directly from the data are very valuable.

In recent years, the popularity of unsupervised learning has been increasing as a consequence of its capability for extracting relevant information. In this learning approach, an adaptive process leads to solutions that reach maximum similarity among data belonging to the same group (Längkvist et al., 2014). Among the unsupervised techniques, the Self-Organizing Map (SOM) has been widely used for extracting

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information from ecological data (Park and Chon, 2007). SOMs approximate the probability density function of the input data to show the datasets in a more comprehensive lower dimension (Kohonen, 2007). This method has become popular for classification of ecological data in community grouping (Giraudel and Lek, 2001; Park et al., 2003), animal behaviors (Chon et al., 2004), and prediction of population and communities (Obach et al., 2001). However, a SOM yields concrete classifications and only allows single-valued results to discriminate among data. Along with the development of the SOM, other techniques in biologically inspired machine learning have been popularized in data analysis in ecology. Methods based on many-valued logic, specifically fuzzy set theory, have been efficiently used for extracting information from data. Among the existent classification techniques, those that include fuzzy logic have the advantage of expressing the membership degree of each datum to several clusters (Futschik and Kasabov, 2002). They also provide easily interpretable results and are known for their ability to model knowledge, uncertainty, and imprecision (Gentil, 2007). In 2006, Adriaenssens et al. (2006) used fuzzy knowledge-based models for prediction of macro-invertebrates in watercourses; while Chen and Hare (2006) used neural networks and fuzzy logic models for analysis of the pacific halibut recruitment. These were fuzzy rule-based models created to capture the previously collected knowledge about the ecological issue, in order to deal with the uncertainty and imprecision of the data. Within the best of our knowledge, research on methods capable of identifying species not included in the training data based on fuzzy analysis of animal calls have not been reported in the literature. Additionally, none of these methodologies is able to automatically generate clusters based on non-identified species detection.

Fuzzy clustering allows associating animal species by estimating call similarities through acoustic features extracted from the mating calls. The Learning Algorithm for Multivariate Data Analysis (LAMDA) (Aguilar-Martin and López de Mantarás, 1982) is a fuzzy methodology based on conceptual clustering (Biswas et al., 1998). It has been typically used in monitoring task applications (Bedoya et al., 2012; Lamrini et al., 2011; Olivier-Maget et al., 2009), and in recent years, it has been used as a useful tool in medical and biological applications (Hedjazi et al., 2013; Uribe et al., 2011). LAMDA is an unsupervised training algorithm, which does not require defining the number of clusters as an input parameter, such as other unsupervised fuzzy clustering algorithms. Additionally, it allows the addition of new clusters to detect non-established patterns in training, without repeating the learning phase. LAMDA creates new clusters when the input data cannot be assigned to one of the clusters generated in the training stage. The new clusters are initialized with the parameters of these unrecognized data and modified according to the new entries during the remaining classification process.

Recent studies have implemented pattern recognition techniques in order to detect animal calls (also known as advertisement calls, or chants): Cheng et al. (2010) proposed a call-independent automatic acoustic system for individual recognition of animals using Mel Frequency Cepstral Coefficients (MFCCs) (Mermelstein, 1976) as acoustic features, and Gaussian Mixture Models (GMM) as classification technique. They achieved accuracies between 89.1% and 92.5% applying their methodology to the avian sound identification, but it was sensitive to noise. Similarly, Acevedo et al. (2009) used statistical features (minimum frequency, maximum frequency, maximum power and call duration) to compare the effect of three different classification techniques—Linear Discriminant Analysis (LDA), Decision Trees (DT), and Support Vector Machines (SVM)—on the identification of amphibian and avian sounds. Accuracies achieved fluctuated between 72.45% and 94.95% and were highly dependent of the selected classification technique (relatively low and high accuracies for LDA and SVM, respectively). In the same way, Chang-Hsing et al. (2006) used LDA but with non-statistical features (MFFCs) for amphibian identification (30 frog species), showing an improvement in the accuracies to 96.8% and 97.4%.

Among the wide variety of animal species, and given their cryptic behavior in many species, anurans become an excellent model for population monitoring through bioacoustics. Currently, there is an interest for identifying anuran species from their advertisement calls; nonetheless, existent methods do not allow the classifier to identify species that were not presented in the training stage. Whether to identify additional species (found after learning) is required, the training stage must be repeated (increasing the computational cost). In this paper, a new approach for an automatic and unsupervised call recognizer of anuran species using fuzzy clustering and MFCCs is introduced. It is able to identify unknown species that were not present in the training stage, and to establish relations among species of the same genus through their membership degrees.

This paper is presented as follows: Section 2 explains the theory related with the presented methodology and used materials; in Section 3 results are presented and discussed. Finally, in Section 4 conclusions and future work are expressed.

2. Materials and methods

2.1. Materials

Two datasets constituted by 916 calls of 13 anuran species provided by the Smithsonian Tropical Research Institute (STRI) (Ibañez et al., 1999) and the Grupo Herpetológico de Antioquia (GHA) were selected for this study. From the STRI dataset (103 of the 916 calls; SR = 44100 Hz), only those species located in Colombia (Chocó department) with a significant number of calls were selected: *Bufo typhonius* (*Rhinella margaritifer*) (BF) (Le = 0.75s; Fo = 1625.6 Hz, where Le and Fo are the mean length and mean dominant frequency of the calls, respectively), *Eleutherodactylus diastema* (*Diasporus diastema*) (ED) (Le = 0.20 s; Fo = 3045.7 Hz), *Hyla boans* (*Hypsiboas boans*) (HB) (Le = 0.81 s; Fo = 506.2 Hz), *Leptodactylus fuscus* (LF) (Le = 0.32 s; Fo = 2240.9 Hz), *Leptodactylus pentadactylus* (*Leptodactylus savagei*) (LP) (Le = 0.34 s; Fo = 500.4 Hz), *Scinax ruber* (SR) (Le = 1.92 s ; Fo = 835.1 Hz) and *Dendrobates auratus* (DA) (Le = 4.70 s; Fo = 1575.8 Hz).

A new dataset (Antioquia; freely available by contacting the corresponding author) with 813 calls of six anuran species, obtained in the eastern Antioquia by the GHA, was also used. All data were recorded with a Sennheiser ME66 directional microphone, SR = 44100 Hz (see Fig. 1). It consisted of 153 calls of *Diasporus anthrax* (DAN) (Le = 0.04 s; Fo = 4101.4 Hz), 67 calls of *Dendrobates truncatus* (DT) (Le = 0.61 s; Fo = 2939 Hz), 76 calls of *Diasporus gularis* (DG) (Le = 0.14 s; Fo = 2870.6 Hz), 344 calls of *Engystomops pustulosus* (EP) (Le = 0.15 s; Fo = 1516.0 Hz), 92 calls of *Colostethus* aff. *fraterdanieli* (CF) (Le = 0.12 s; Fo = 4593.4 Hz), and 81 calls of a *Pristimantis* sp. nov. (PS) (Le = 0.03 s; Fo = 3064.4 Hz).

In both datasets a directional microphone was used for recording the advertisement calls, in order to avoid the segmentation of non-desired sounds from the rest of the community. This facilitates the recognition process—in comparison with omnidirectional microphones—and ensures that the feature extraction and the classification were performed only on anuran calls. However, the recordings are far from being totally noiseless (see Fig. 1) and a noise reduction stage had to be added with the purpose of enhancing the segmentation procedure.

Chocó-Darién and Antioquia datasets were segmented, noise-reduced, and classified using the methodology presented below. All algorithms were programmed in Matlab 2013b.

2.2. Study area

Calls from the Chocó-Darién region were recorded at Monumento Nacional Barro Colorado, Panama (9°09′N, 79°51′W). This site is a lowland tropical rainforest with a diverse amphibian community. Data from Antioquia were recorded in the Andes on the eastern

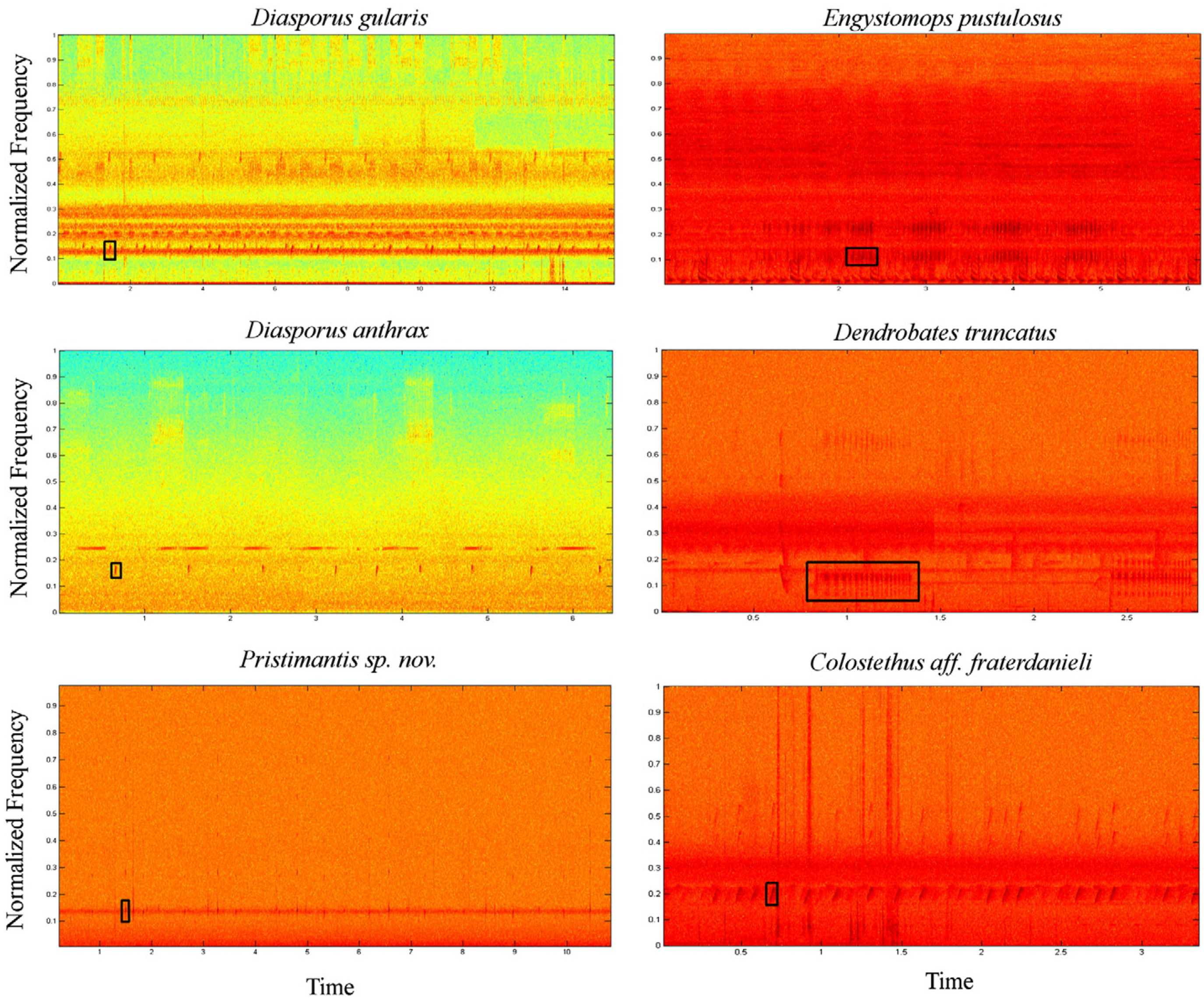

Fig. 1. Time–frequency representation (spectrogram) of several recordings with the species from the Antioquia region (black frames indicate call examples). *Diasporus gularis*, *Engystomops pustulosus*, *Colostethus* aff. *fraterdanieli* and *Dendrobates truncatus* recordings showed more acoustic interference produced by the community.

flank of the northern Cordillera Central in Antioquia, Colombia (6°33′N, 64°56′W; 6°22′N, 75°08′W; 6°11′N, 74°59′W). The area is found in low and mid elevations (700 to 1200 masl) with moderately disturbed forests.

2.3. Case studies

Two case studies for testing the proposed methodology were designed. In the first case study (Chocó-Darién region), the dataset was divided in two subsets of proportions 70% (71 calls) and 30% (31 calls) for training and recognition respectively. Additionally, one *Dendrobates auratus* (DA) call was used together with two DA calls of the Encyclopedia of Life (Encyclopedia of Life, 2014) to show the relation between the advertisement calls among the species of the same genus.

In the second case study (Antioquia region) a larger dataset recorded in field with 813 calls of six different anuran species was used to challenge the methodology, as the Chocó-Darién dataset only counts with 113 calls (a relatively small amount).

2.4. Methodology

The proposed methodology analyzes recordings where existence of anuran calls is plausible. It consists of four main stages (see Fig. 2): The first stage reduces the background noise (e.g., rain, wind, creeks) in order to benefit the result of the segmentation of the advertisement calls (second stage). The third stage performs the extraction of acoustic features (i.e., acoustic properties of the calls with high variability inter-species and low variability intra-species), with the purpose of maximizing differences among anuran species. Finally, in the fourth stage a classifier analyzes the previously extracted features for each call, in order to determine whether the selected call corresponds or not to a pre-established cluster (species).

2.4.1. Noise reduction

This noise reduction stage uses the spectral noise gating methodology (Chen et al., 2009) for estimation and suppression of undesired components in the selected frequency band spectrum of the signal (recordings where anuran calls possibly exist). It consists of two

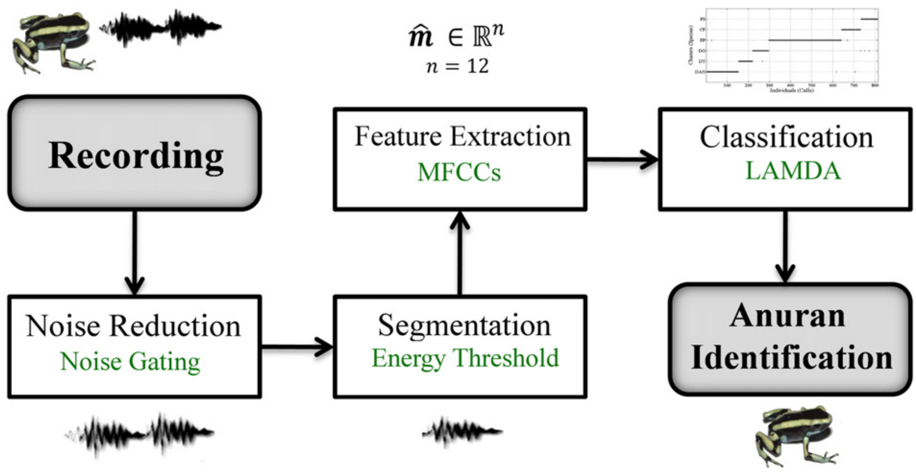

Fig. 2. Call recognition system. Each recording of the anuran species is noise-reduced and segmented to obtain each advertisement call individually separated. Then the MFCCs of each call are extracted to be classified by means of LAMDA classification methodology. Finally, each call is assigned to one of the clusters and related with one of the expected anuran species.

principal stages (Fig. 3): threshold estimation and noise removal. The threshold estimation is performed over a pure-noise section of the signal, i.e., a segment of the recording without the waveform of interest (advertisement calls). The noisy section—in this case the first 0.5 s of the recording—was intentionally captured during the database acquisition process with the purpose of transforming the threshold estimation step in an automatic procedure. This procedure consists on applying the fast Fourier transform (FFT) in $\boldsymbol{w}_p \in \mathbb{R}^{lw}$, $p = 1, \ldots, P$ finite intervals (windows) of the noisy section of the recorded waveform, where lw is the length of the window. Then, the maximum amplitude level per frequency band of all $\boldsymbol{w}_p$ windows is stored in a dictionary and used as threshold in amplitude for the whole recording.

During the noise removal stage, the gain control for each frequency band is established in such a way that if the recording has exceeded the threshold, the gain is set to 0 dB (same input and output amplitude); otherwise the gain is set to a lower value (−22 dB) in order to suppress the noise (i.e. those band frequencies without significant activity are neglected but not turned to zero because the elimination of spectral content is not desired when a mating call and background noise are contained in the same window). Gain controls are applied to the complex FFT of the signal, and then the inverse FFT followed by a Hamming window is applied (Mottaghi-Kashtiban and Shayesteh, 2011). Afterwards, the output signal $\boldsymbol{x} \in \mathbb{R}^a$, where a is the length of the recording, is reconstructed by overlapping (one half) the hamming windows. A Hamming window is a finite time interval whose shape is optimized to reduce the spectral leakage (undesired frequencies as consequence of the windowing).

After performing the noise reduction stage, the signals are segmented in order to separate each individual call of the residual noise. Natural noises that can be correctly characterized and are not present in the range of frequencies of the studied anuran species (e.g., human voice) were filtered.

2.4.2. Segmentation

The syllable is the most appropriate hierarchical division of the original advertisement call that could be used for species recognition (Cheng et al., 2010). Syllable segmentation consists on isolating the previously noise-reduced signal $\boldsymbol{x}$ into $b = 1, \ldots, B$ small segments: $\boldsymbol{s}_b \in \mathbb{R}^{ls}$, product of independent vocalizations (syllables) for an easier analysis or processing in the following stages, where ls represents the length of the syllable in samples (ls is variable as consequence of its dependence on the length of the call). This technique compares the energy of the signal with a threshold value. It identifies the start of the call as the point at which the energy first exceeds the threshold and the end as the point at which the energy drops below the threshold (Cheng et al., 2010). Each datum of the energy $\boldsymbol{E}$ is calculated using a sliding window of size w:

$$E_v = \sum_{i=1}^{w} |x_i|^2 \tag{1}$$

where E_v is the v-th datum of $\boldsymbol{E}$, and x_i is the i-th datum of the window (i.e., a sample of the noise-reduced waveform). The signals were centralized (mean value equal zero) before computing the energy in order to suppress the influence of the baseline (caused by background noise), and to emphasize the effect of energy calculations in signal amplitude changes. The Root Mean Square (RMS) value of the energy R (see Eq. (2)) was used as threshold:

$$R = \sqrt{\frac{1}{le} \cdot \sum_{v=1}^{le} {E_v}^2} \tag{2}$$

where $v = 1, \ldots, le$, and le is the length of the energy signal $\boldsymbol{E}$.

2.4.3. Feature extraction

In most cases the clustering algorithm does not yield good classification results when pure signals taken from the recordings are directly used in it (Candolfi et al., 1999). Therefore, a pre-processing stage is needed in order to obtain a pattern space able to distinguish among species.

Human auditory perception does not follow a linear scale; the perception of some frequencies is highly influenced by energy in the critical band of frequencies around them (Cheng et al., 2010). Similarly occurs in anurans (Chung et al., 1978; Pettigrew et al., 1978); therefore, their perception of auditory stimuli cannot be assumed as a linear and equitable distribution of the band spectrum. Mel Frequency Cepstral Coefficients (MFCCs) emerged as a solution for this issue. They redistribute the frequencies across the spectrum in order to benefit specific bands before the filtering application.

MFCC features are widely used in automatic human speech and speaker recognition. Also, their application to species identification has given promising results across a variety of animals including frogs, crickets, and birds (Chang-Hsing et al., 2006; Cheng et al., 2010; Fox et al., 2006). They provide several advantages over the commonly used time-frequency features (mean fundamental frequency, maximum frequency, minimum frequency, syllable energy, syllable duration, zero-crossing rate, and similar ones). The advantages of using MFCCs include, inter alia, small variation over time, high accuracy, and recognition regardless of the call type (Fox, 2008).

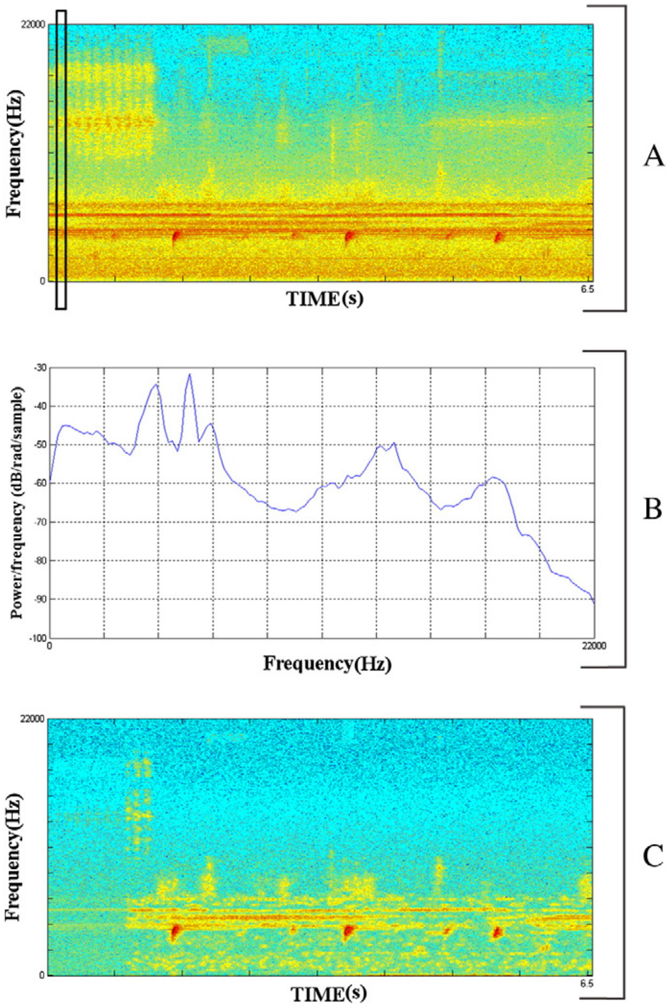

Fig. 3. Noise reduction stage. (A) Section of a recording with three calls of *Diasporus anthrax*; black frame indicates one of the $\boldsymbol{w}_p$ windows in which the noise is estimated. (B) Power spectral density of a noisy section (black frame in A); the maximum values of each frequency band are stored in a dictionary in order to establish a threshold. (C) The threshold is applied to the original recording with the purpose of obtaining the noise-reduced signal. The noise of the recordings was almost entirely suppressed after using this noise reduction method.

The MFCC feature extraction process is explained as follows (Mermelstein, 1976):

(i) The b-th syllable of $\boldsymbol{s}_b$ is sliced in $c = 1, \ldots, C$ shorter excerpts called frames: $\boldsymbol{f_c} \in \mathbb{R}^{lf}$, of length lf. Typically, the spectral content is not present in the complete segment, but only during a certain time window. Thus, inaccuracies in the original segmentation are corrected. The length of the frame lf is a fixed parameter, but the number of frames depends on the length of the syllable ls.

(ii) The Fourier transform, for d pre-defined frequencies, is taken for each of these excerpts in order to calculate the power spectrum. Consequently, the frequency bands of interest in the frame are identified.

(iii) The power spectrum is mapped to the Mel-frequency scale (Eq. (3)). In the Mel-scale the frequency bands are not equally spaced, which is more approximated to the response of the animal auditory system (e.g., some individuals are unable to discern the difference between two closely spaced frequencies).

$$\boldsymbol{v}_{\mathbf{mel}} = \frac{1000}{\log(2)} \cdot \log\left(1 + \frac{\boldsymbol{v}_{\mathbf{freq}}}{1000}\right) \tag{3}$$

where $\boldsymbol{v}_{\mathbf{mel}} \in \mathbb{R}^d$ is a vector of the original frequencies $\boldsymbol{v}_{\mathbf{freq}} \in \mathbb{R}^d$ mapped to a Mel frequency scale.

(iv) A Mel-spaced filter-bank of z filters (algorithm parameter) is applied along the modified power spectrum in order to identify the existing energy in each frequency region. For the methodology proposed in this paper, selected filters are triangular, half overlapping, with center frequencies uniformly distributed along the Mel frequency scale.

(v) The log of the energy of each filter is obtained. The sound intensity is not perceived in a linear scale by the auditory system of the studied species, then, it should be taken into account.

(vi) The discrete cosine transform (DCT) of each log of energy is taken. Filter-bank energies are quite correlated with each other because the filters of the filter-bank are all overlapping. The DCT is responsible to decorrelate the energies.

(vii) Only the lower 12 DCT values are kept. This because increasing the accuracy of the parametric representation by adding parameters (12 or more) leads to an increment of complexity and eventually does not lead to better results due to stability issues. The larger the number of parameters in a model, the larger the training sequence (Mermelstein, 1976).

(viii) The resultant n features (in this case 12 scalar numbers) are called Mel Frequency Cepstral Coefficients $\boldsymbol{m} \in \mathbb{R}^n$, with $n = 12$, and they are calculated for every c-th frame excerpted from the b-th syllable of $\boldsymbol{s}_b$. MFCCs can be understood as a modification of the conventional cepstrum in order to adapt the signal processing to the vocal specificities of the studied species (anurans). It emphasizes the frequency bands where their vocal apparatus works. The feature extraction is illustrated in Fig. 4.

(ix) Finally, the mean value of the MFCCs of all C frames is calculated, obtaining a vector $\overline{\boldsymbol{m}} \in \mathbb{R}^n$ per syllable. Then it is normalized (Eq. (4)) and used as input for the classification stage.

$$\hat{m}_j = \frac{\overline{m}_j - \overline{m}_{\min}}{\overline{m}_{\max} - \overline{m}_{\min}} \tag{4}$$

where $\overline{m}_{\min}$ and $\overline{m}_{max}$ are the minimum and maximum values of $\overline{\boldsymbol{m}}$ respectively, $\hat{\boldsymbol{m}} \in \mathbb{R}^n$ is the vector $\overline{\boldsymbol{m}}$ normalized, and $\hat{m}_j$ is the datum belonging to the j-th MFCC in $\hat{\boldsymbol{m}}$.

Due to the high accuracy results obtained, only 12 MFCCs were used. Delta and Double-Delta (parameters commonly used in Automatic Speech Recognition) were not employed because they improved neither the classification results nor the processing time.

2.4.4. Classification

The classifier is responsible for identifying clusters related to the anuran species that produced the call. Classifiers are often developed in two stages: training, where examples are used to generate each cluster (related to species) and classification, where new calls are identified in order to associate them with an existent cluster.

For the classification task, LAMDA—Learning Algorithm for Multivariate Data Analysis (Aguilar-Martin and López de Mantarás, 1982)—was used. It is based on finding the global adequacy degree of an element to an existing cluster (in this case species) considering all the contributions of each of its attributes (the 12 identified MFCCs). As a consequence of being fuzzy based, LAMDA obtains all necessary information from the data and not from the rules, which govern the behavior of the system. Furthermore, LAMDA is not a distance based method; it performs a similitude analysis among data to establish the relation between every particular datum with its respective cluster. It can handle information with uncertainty and vagueness, even when the expert is unable to define all the rules. It does not require the number of clusters (i.e., the number of anuran species) as input parameter as most of the fuzzy clustering algorithms (e.g., Fuzzy C-Means or GK-Means). Furthermore,

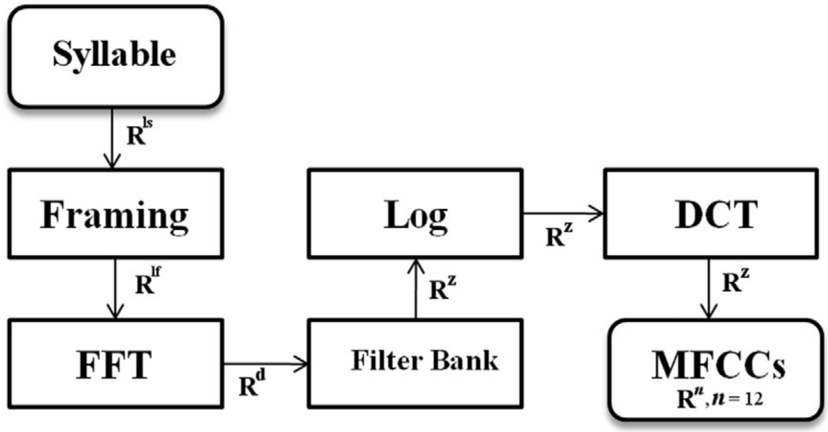

Fig. 4. Feature extraction—MFCC estimation. Each frame of the syllable is frequency-transformed, processed through a Mel-spaced filter bank and then decorrelated using a discrete cosine transform in order to obtain the Mel Frequency Cepstral Coefficients.

LAMDA estimates the membership degree of a call (datum) to a species (cluster) in a non-iterative process (results are obtained solely with one data reading), reducing computational cost and avoiding time consumption.

This algorithm is based on the use of adequacy degrees in order to establish a data representation in clusters. The contribution of each feature (MFCC in this case) is called the marginal adequacy degree (MAD). The MAD M_{lj} of each j-th descriptor $\hat{m}_j$ to each l-th cluster is estimated using Eq. (5):

$$M_{lj} = \rho_{lj}{}^{\hat{m}_j}\left(1-\rho_{lj}\right)^{1-\hat{m}_j} \tag{5}$$

where $\hat{m}_j$ is the datum belonging to the j-th MFCC in$\hat{\boldsymbol{m}}$, $\boldsymbol{\rho} \in \mathbb{R}^{h \times n}$ is a matrix with the mean values for each j-th MFCC in each l-th cluster (species) respectively, ρ_{lj} is the element belonging to the l species and to the j-th MFCC in the $\boldsymbol{\rho}$ matrix, h is the number of clusters, and n is the number of features.

Marginal adequacy degrees (MADs) from all clusters constitute the matrix $\boldsymbol{M} \in \mathbb{R}^{h \times n}$. It is combined using fuzzy logic connectives (max, min) as aggregation operators in order to obtain the Global Adequacy Degree GAD (Piera-Carrete et al., 1990) of an element (advertisement call) to a cluster (species), taking into account the contribution of all descriptors (see Fig. 5). This value corresponds to the membership degree of a call to a cluster. After calculating the MADs, the GADs $\boldsymbol{g} \in \mathbb{R}^{h}$ are calculated using aggregation rules established by logical connectors:

$$g_l = (\alpha)T\left(M_{l1}, \ldots, M_{lj}, \ \ldots, M_{ln}\right) + \ (1-\alpha)S\left(M_{l1}, \ldots, M_{lj}, \ \ldots, M_{ln}\right) \tag{6}$$

where g_l is the GAD associated to the species l in $\boldsymbol{g}$, $T(M_{l1}, \ldots, M_{lj}, \ldots, M_{ln})$ is the T-norm (min $(M_{l1}, \ldots, M_{ln})$), $S(M_{l1}, \ldots, M_{lj}, \ldots, M_{ln})$ is the S-norm (max $(M_{l1}, \ldots, M_{ln})$), $0 < \alpha < 1$ is an exigency index (factor responsible to adjust the influence of the T-norm and S-norm in the aggregation), and l is the current cluster (anuran species). An advertisement call is assigned to the species that exhibits the maximum GAD.

Internally, the procedure for using LAMDA is divided in two steps: training and classification.

— Training:

The algorithm is initialized with only one predefined cluster

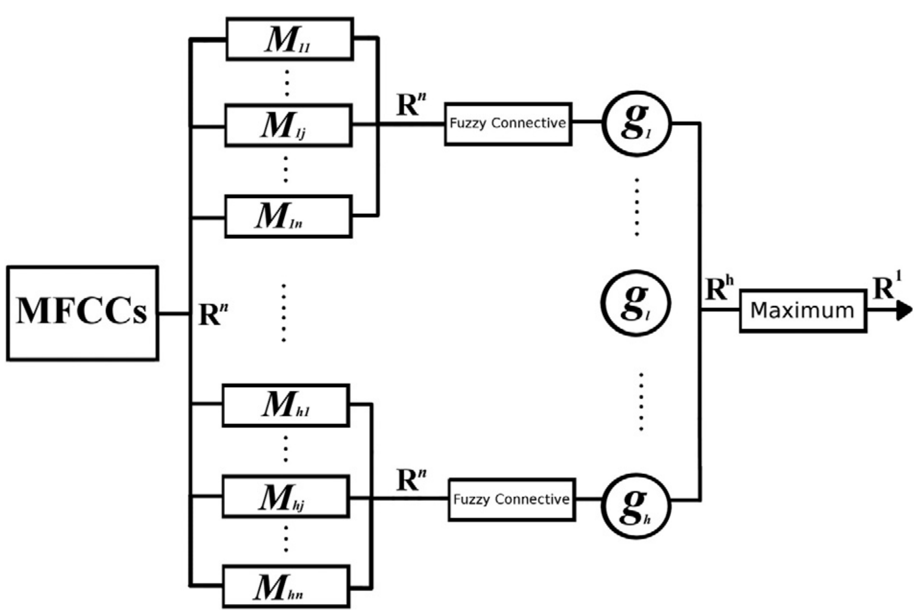

Fig. 5. LAMDA Scheme. The algorithm uses the acoustics features found in the feature extraction stage as input. Then, the MADs are computed and aggregated by means of fuzzy connectives with the purpose of obtaining the membership degrees (GADs). As a result, the call is assigned to the cluster with the maximum GAD value.

commonly known as the Non-Information cluster (NIC), cluster 0 in this case, with $\rho_{0j} = 0.5\ \forall j = 1, \ldots, n$. The first element (anuran call) is classified in the NIC because it is considered unrecognized. Then, a new cluster ($l = 1$) is created using Eq. (7), and the mean values $\rho_{lj}[k]$ of the first step $k = 1$ are initialized with the NIC parameters ($\rho_{lj}[k-1] = 0.5\ \forall j = 1, \ldots, n$) and $n_l[k-1] = 1$. Subsequently, a new call is entered at updated step k, and the GADs are calculated with the values ($\hat{m}_j[k]$) of the new call. Whether the call is assigned to the NIC (i.e., maximum GAD corresponds to the NIC cluster), a new cluster is created and initialized with the NIC parameters modified by the data values as additional information. Otherwise, the mean values of the previously created cluster ($\rho_{lj}[k-1]\ \forall j = 1, \ldots, n$) are updated with the values of that element in order to contain the new entry value (in this case $n_l[k-1]$ is the number of calls previously classified in this cluster).

$$\rho_{lj}[k] = \rho_{lj}[k-1] + \left[\frac{\hat{m}_j[k] - \rho_{lj}[k-1]}{n_l[k-1] + 1}\right] \tag{7}$$

Where $\rho_{lj}[k]$ is the updated mean value for the j-th MFCC in the l-th species respectively, $\rho_{lj}[k-1]$ is the preceding ρ_{lj} value (the same used for calculating MADs in Eq. (5)), and $n_l[k-1]$ is the number of elements previously classified in cluster l.

This process continues until all training calls have been analyzed.

— Classification:

Once the classifier is trained a new entry (call) is analyzed (using Eqs. (5) and (6)) and its adequacy degrees to all species are estimated (GADs). The call is assigned to the species that exhibits the maximum GAD.

If the cluster with the maximum membership degree (GAD) is the NIC, a new cluster is created as a non-identified species. For this reason, the methodology is able to find unknown species that were not included in the training stage.

2.4.5. Algorithm setup

Methodology parameters were selected based on the combination that presents the highest accuracy. In the noise reduction stage, parameter l_w (length of the window) was chosen equal to 10 ms. For segmentation $w = 10$ samples were selected. 12 MFCCs per frame $\boldsymbol{f_c}$ of each syllable $\boldsymbol{s_b}$ were extracted (Lee et al., 2006). Each frame had a $lf = 20$ ms and $lf = 10$ ms length for Chocó-Darién and Antioquia respectively with 10 ms of overlapping for both datasets; z parameter was selected as 40. The exigency index α depends on the used dataset (1 and 0.5 for Chocó-Darién and Antioquia respectively).

3. Results and discussion

In Chocó-Darién the methodology was trained in order to find the most appropriated clusters to assign each of the analyzed calls, and then new data (calls) were used to test the effectiveness of the found clusters. As a final step, calls from species—not included in the training data—were aggregated to test the class generation feature of the methodology. In Antioquia, a different (larger) dataset was used with the purpose of detecting, without any training, all the advertisement calls of the different species.

3.1. Chocó-Darién Region

I. Training stage: Acoustic features ($n = 12$ MFCCs) per each of the 71 training recordings (70% of total data) were extracted. Subsequently, a classifier (LAMDA, $\alpha = 1$ in Eq. (6)) to distinguish among feature vectors was trained. 100% of accuracy in all individuals (calls) of all clusters (species) was attained. Table 1 shows the training and recognition results of the proposed methodology.

II. Recognition stage: After training, the data reserved for testing the methodology (30% of total data) were used; obtaining 100% of accuracy for all individuals. Table 1 shows that all calls from both subsets (recognition and training) were correctly classified in their correspondent species. This result exhibits that the proposed methodology is useful as discriminator among anuran species.

III. Validation: Finally, the classifier was used to identify new recordings. The addition of new clusters is possible as consequence of the non-required retraining characteristic of the methodology. In this stage, new data with additional species not presented in the training stage was added. Three calls belonging to *D. auratus* (DA) species were used, one taken from the Chocó-Darién dataset and two provided by an external dataset (Encyclopedia of Life, 2014). The data were recognized as belonging to a new species (a new cluster) by the classifier. Additionally, 9 data (calls) provided by the GHA of the *D. truncatus* (DT) species were used. With these data 100% accuracy was achieved. Advertisement calls of species not presented in training were correctly recognized as non-identified species (Table 1). *D. truncatus* calls were recorded with different microphones in different areas. However, even under these different conditions the methodology presented an exceptional performance.

Considering the application accounted in this study, in several cases it is better not to fix the number of clusters in the classification algorithm. Although the expert (biologist) searches some specific clusters (species), it should be better to apply an unsupervised learning since other unexpected species could be detected. The proposed methodology is able to include new clusters without repeating a learning phase. This attribute is used to find unexpected species of anurans in the recordings: if a call cannot be classified among the found species in training, a new cluster is created as a non-identified species. In this case the methodology found the DA and DT species, but it could also be related to a previously non-reported species.

DA and DT data were selected because these two species belong to the same genus (*Dendrobates*) and their advertisement calls are similar. Sister species can retain call features as sexual selection in conspecifics is not operating in these geographically separated (allopatric) species. For example, we observed in field works that *D. truncatus* males respond to *D. auratus* calls, indicating that these individuals are unable to differentiate conspecifics from heterospecifics. Nonetheless, the proposed methodology was able to differentiate between the two matting calls.

An additional advantage of the proposed methodology is its capability of finding similarities among individuals of different clusters. Table 2 shows the GADs (or membership degrees) of 12 selected data (calls) to each cluster (species). The higher the membership degree (compared among themselves), the closer the relationship between the advertisement call and the species. The highest GADs of the last three rows (10th–12th) coincided with the

Table 1
Training and recognition results. 100% of accuracy in training and recognition with the Chocó-Darién dataset was achieved. None datum (anuran call) was inappropriately classified in a different species. *Dendrobates truncatus* and *Dendrobates auratus* (clusters 7th and 8th) were created as consequence of not fulfilling the requirements for belonging to any of the pre-existent species (as it was expected).

Cluster	Species	Training	Recognition
1	*Rhinella margaritifer(BF)*	100%	100%
2	*Diasporus diastema(ED)*	100%	100%
3	*Hypsiboas boans(HB)*	100%	100%
4	*Leptodactylus fuscus(LF)*	100%	100%
5	*Leptodactylus savagei(LP)*	100%	100%
6	*Scinax ruber(SR)*	100%	100%
7	*Dendrobates truncatus(DT)*	N/A	100%
8	*Dendrobates auratus(DA)*	N/A	100%

Table 2
Global adequacy degrees for recognition. The red frame shows the relation through the membership degrees between *Dendrobates auratus* and *Dendrobates truncatus*. The cluster with the second highest membership degree to DA is the DT species.

	GAD ($\times 10^{-5}$)							
CALL	BF	ED	HB	LF	LP	SR	DT	DA
1 (DT)	0.03	2.69	0.01	0.01	0.01	0.24	7.82	0.71
2 (DT)	0.04	2.82	0.01	0.01	0.01	0.26	9.05	0.78
3 (DT)	0.03	4.67	0.02	0.02	0.02	0.27	12.28	0.77
4 (DT)	0.02	5.96	0.01	0.01	0.01	0.22	17.17	0.59
5 (DT)	0.03	2.40	0.02	0.03	0.02	0.19	7.70	0.44
6 (DT)	0.06	2.11	0.00	0.01	0.00	0.24	9.69	0.95
7 (DT)	0.06	2.03	0.01	0.02	0.00	0.27	8.77	0.92
8 (DT)	0.05	2.26	0.01	0.02	0.00	0.26	10.08	0.94
9 (DT)	0.04	2.48	0.01	0.01	0.00	0.23	10.31	0.70
10 (DA)	0.12	0.88	0.13	0.01	0.00	0.22	1.56	33.99
11 (DA)	0.13	0.88	0.10	0.00	0.00	0.23	1.32	79.31
12 (DA)	0.16	0.25	0.06	0.02	0.03	0.70	2.78	11.43

individual of the species that produced the call (i.e., DA) with values of 33.99×10^{-5}, 79.31×10^{-5}, and 11.43×10^{-5} corresponding to 92.09%, 93.75%, and 74.08% of membership to its own cluster. Also, the second highest GADs (1.56×10^{-5}, 1.32×10^{-5}, and 2.78×10^{-5} corresponding to 4.23%, 1.61%, and 18.02% of membership) is related to the most similar species (DT). This implies that the presented methodology is able to detect correlations among species of the same genus by means of their advertisement calls, as long as they have similar articulation and phonetic capabilities. This is a useful feature for identifying species, especially when they are unknown.

These remarkable results (100% of accuracy) must be carefully observed. They suggest that the proposed methodology is highly accurate, but this achievement would be due to several particular characteristics of the dataset (non-interference, low noise, easily differentiable species). In order to provide a wider validation of this methodology, in the following section a new dataset acquired under different conditions is tested.

3.2. Antioquia Region

For challenging the methodology, a different dataset (Antioquia) with 813 calls of six anuran species was used. An initial test performed with the algorithm parameters of Chocó-Darién ($\alpha = 1$) achieved a total accuracy of 95.20% in all species (see Table 3A). It implies a low dependence between the used dataset and the parameters of this methodology. Nevertheless, when the methodology was retrained with parameters more accurate to the dataset specificities ($\alpha = 0.5$, $\text{lf} = 10$ ms) the accuracy reached a value of 99.61% (Tables 3B and 4).

The results of the methodology reached high values of accuracy (99.61% in average performance; see Table 4) and only few data were misclassified. Table 3B shows the confusion matrix for the Antioquia dataset; in this matrix, it is possible to observe that only one datum of DAN, one datum of DG, one datum of EP, two data of PS, and five data of CF were erroneously classified in other species. The advertisement calls of CF and DAN had almost the same dominant frequency; additionally, the calls of CF, DAN, DG, and PS had similar time length and spectrum distributions (i.e., most of their harmonics were overlapped). This, in accumulation with the intra-specific frequency variations of the individuals, induces some false positives and false negatives in the results of the methodology. In addition, the misclassified calls in EP and DT were mostly consequence of a high level of background noise that could not be entirely reduced.

Sensitivity (*Sen*), specificity (*Spe*), and accuracy (*Acc*) were used to test the performance of the methodology (see Table 4); they are defined by:

$$Sen = \frac{TP}{TP + FN}, \quad Spe = \frac{TN}{FP + TN}, \quad Acc = \frac{TN + TP}{TN + TP + FN + FP} \tag{8}$$

where *TP* is the number of true positives, *TN* is the number of true negatives, *FP* is the number of false positives, and *FN* is the number of false negatives.

Tables 1 and 4 evidence a high accuracy in the classification results for Antioquia and Chocó-Darien databases. In both cases a directional microphone, together with a noise reduction algorithm, instead of an omnidirectional microphone, was used. This avoided the segmentation of non-desired sounds from the rest of the community, facilitating the recognition process and ensuring that the feature extraction and classification were performed only on anuran calls. Due to this, the clustering algorithm only focused on vocalization recognition and not in vocalization recognition, bad segment identification, and noise discarding. The unsupervised multi-cluster recognition and after-training cluster addition of this methodology were possible, in certain part, to the well acquired database and the good performance of the noise reduction and segmentation stages.

4. Conclusions and future work

In this study, a new methodology for detecting and identifying different anuran species using MFCCs and fuzzy clustering was presented. This methodology allows training with data recorded in different environments and recorders. Nonetheless, complex amphibian communities (i.e., tropical assemblages)—where call interference and similarity among advertisement calls of species could make more difficult the species recognition—will challenge the methodology in its goal of detecting the different species. On the other hand, the parameters do not need to be adjusted when the amphibian species composition change along latitudinal and habitat gradients, even if the advertisement call within a

Table 4
Classification results with the Antioquia dataset (best parameters: $\alpha = 0.5$, $lf = 10$ms). 813 calls of six anuran species were used to test robustness in the proposed methodology; only 10 data were incorrectly classified (sensitivity of 98.30%). Clusters 6 and 7 showed a specificity of 100%, indicating that there were not false negatives associated to these clusters. The general accuracy of the methodology applied to the Antioquia dataset was 99.61%.

Cluster	Species	# Calls	Sensitivity	Specificity	Accuracy
1	*Diasporus anthrax(DAN)*	153	99.35%	99.55%	99.51%
2	*Dendrobates truncatus(DT)*	67	100.00%	99.87%	99.88%
3	*Diasporus gularis(DG)*	76	98.68%	99.59%	99.51%
4	*Engystomops pustulosus(EP)*	344	99.71%	99.57%	99.63%
5	*Colostethus aff. fraterdanieli(CF)*	92	94.57%	100.00%	99.38%
6	*Pristimantis sp. nov.(PS)*	81	97.53%	100.00%	99.75%
	Average performance	813	98.30%	99.76%	99.61%

Table 3
Confusion matrices for the Antioquia dataset. (**A**) $\alpha = 1$, $lf = 20$ms, (**B**) $\alpha = 0.5$, $lf = 10$ms. In (**B**) *Dendrobates truncatus* (DT) does not present false positives (100% sensitivity), while *Colostethus* aff. *fraterdanieli* (CF) and *Pristimantis* sp. nov. (PS) do not present false negatives (100% specificity).

		Predicted					
		DAN	***DT***	***DG***	***EP***	***CF***	***PS***
Actual	***DAN***	150	0	0	0	0	3
	DT	0	66	0	0	1	0
	DG	0	4	71	0	0	1
	EP	5	0	0	330	9	0
	CF	3	0	0	0	85	4
	PS	0	0	10	0	0	71
(A)							

		Predicted					
		DAN	***DT***	***DG***	***EP***	***CF***	***PS***
Actual	***DAN***	152	0	0	1	0	0
	DT	0	67	0	0	0	0
	DG	0	1	75	0	0	0
	EP	1	0	0	343	0	0
	CF	2	0	1	2	87	0
	PS	0	0	2	0	0	79
(B)							

species change across its entire distribution. This methodology does not only identify the advertisement calls, but also accepts the addition of new clusters associated to species not included in the training stage. It does not require all data to perform its analysis; giving it a high capability for working with large amounts of data and single-datum analysis (other methods cannot achieve it without repeating a learning stage). This is a novel way to identify new species of anurans, by creating a new cluster (species) if a call cannot be related with the ones presented in the training phase. Due to this feature, two additional species not included in the training data (*D. auratus*—DA—and *D. truncatus*—DT) were identified. Additionally, through the presented case with DA and DT, it was demonstrated that this methodology is also able to determine correlations among species of the same genus with similar articulation and phonetic capabilities, by means of their calls. An interesting feature when the recognized species is unknown.

Regarding the results of the developed methodology, accuracies between 99.38% and 100% per species were achieved; furthermore, it has shown high noise immunity and excellent potential of recognition among individuals of the same species. Additionally, the parameters of the methodology are continuously adapted by incorporating additional information related with different anuran species. Automatic species recognition will impact not only amphibian bioacoustics research, as it ideally can be extended to more complex animal sounds such as vocalizations of mammals or birds. In addition, ecological questions (e.g., competition, reproduction, natural selection) beyond monitoring programs could be addressed at the community or population level. In future works, this methodology will be implemented with other animal species (it does not analyze specific characteristics of anura order; therefore, it could be easily applied to other animals) focusing on finding non-frequency based acoustic features that may improve the recognition.

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References

Acevedo, M., Corrada-Bravo, C., Corrada-Bravo, H., Villanueva-Rivera, L., Mitchell, A., 2009. Automated classification of bird and amphibian calls using machine learning: A comparison of methods. Ecol. Inf. 4, 206–214.
Adriaenssens, V., Goethals, P.L.M., De Pauw, N., 2006. Fuzzy knowledge-based models for prediction of *Asellus* and *Gammarus* in watercourses in Flanders (Belgium). Ecol. Model. 195, 3–10.
Aguilar-Martin, J., López de Mantarás, R., 1982. The process of classification and learning the meaning of linguistic descriptors or concepts. Approximate Reasoning in Decision Analysis. ,pp. 165–175.
Beausoleil, N., Mellor, D., Stafford, K., 2004. Methods for marking New Zealand wildlife: amphibians, reptiles and marine mammals". Department of Conservation, Wellington, pp. 41–67.
Bedoya, C., Uribe, C., Isaza, C., 2012. Unsupervised Feature Selection Based on Fuzzy Clustering for Fault Detection of the Tennessee Eastman Process. Proceedings of the 13th Ibero-American Conference on Artificial Intelligence (IBERAMIA), Cartagena de Indias, Colombia, pp. 350–360.
Biswas, G., Weinberg, J.B., Fisher, D.C., 1998. Iterate: A conceptual clustering algorithm for data mining. IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. 28, 100–111.
Candolfi, A., De Maesschalck, R., Jouan-Rimbaud, D., Hailey, P., Massart, D., 1999. The influence of data pre-processing in the pattern recognition of excipients near-infrared spectra. J. Pharm. Biomed. Anal. 21 (1), 115–132.
Chang-Hsing, L., Chih-Hsun, C., Chin-Chuan, H., Ren-Zhuang, H., 2006. Automatic recognition of animal vocalizations using averaged MFCC and linear discriminant analysis. Pattern Recogn. Lett. 27, 93–101.
Chen, D., Hare, S.R., 2006. Neural network and fuzzy logic models for pacific halibut recruitment analysis. Ecol. Model. 195, 11–19.
Chen, J., Cohen, I., Huang, Y., 2009. Noise Reduction in Speech Processing. Springer, Berlin.
Cheng, J., Sun, Y., Ji, L., 2010. A call-independent and automatic acoustic system for the individual recognition of animals: A novel model using four passerines. Pattern Recogn. Lett. 43, 3846–3852.
Chon, T.-S., Park, Y.-S., Park, K.Y., Choi, S.-Y., Kim, K.T., Cho, E.C., 2004. Implementation of computational methods to pattern recognition of movement behavior of the German cockroach, *Blattella germanica*, treated with Ca2+ signal inducing chemicals. Appl. Entomol. Zool. 39, 79–96.
Chung, S., Pettigrew, A., Anson, M., 1978. Dynamics of the amphibian middle ear. Nature 272, 142–147.
Encyclopedia of Life, 2014. *Dendrobates auratus,* Available from http://www.eol.org, (Accessed 29 Jan 2014).
Fox, E., 2008. A new perspective on acoustic individual recognition in animals with limited call sharing or changing repertoires. Anim. Behav. vol. 75, 1187–1194.
Fox, E., Roberts, J., Bennamoun, M., 2006. Text-independent speaker identification in birds. Proceedings of the Interspeech 2006 and Ninth International Conference on Spoken Language Processing. vol.1–5, pp. 2122–2125.
Futschik, M.E., Kasabov, N.K., 2002. Fuzzy clustering of gene expression data. Proceedings of the IEEE International Conference on Fuzzy Systems FUZZ-IEEE'02, pp. 414–419.
Gentil, S., 2007. Supervision des procédés complexes; Traité IC2, série Systèmes automatisés. Hermes Science Publications. Lavoisier, Paris.
Giraudel, J.L., Lek, S., 2001. A comparison of self-organizing map algorithm and some conventional statistical methods for ecological community ordination. Ecol. Model. 146, 329–339.
Hassanien, A., Al-Shammari, E., Ghali, N., 2013. Computational intelligence techniques in bioinformatics. Comput. Biol. Chem. 47, 37–47.
Hedjazi, L., Le Lann, M., Kempowsky, T., Dalenc, F., Aguilar-Martin, J., Favre, G., 2013. Symbolic Data Analysis to Defy Low Signal-to-Noise Ratio in Microarray Data for Breast Cancer Prognosis. J. Comput. Biol. 20, 610–620.
Ibañez, R., Stanley, A., Ryan, M., Jaramillo, C., 1999. Vocalizaciones de ranas y sapos del Monumento Natural Barro Colorado, Parque Nacional Soberanía y áreas adyacentes. Sony Music Entertaiment (Central America) S.A.
Kohonen, T., 2007. Self-Organizing Maps. Springer, Berlin.
La Marca, E., Lips, K., Lotters, S., et al., 2005. Catastrophic Population Declines and Extinctions in Neotropical Harlequin Frogs (Bufonidae: Atelopus). Biotropica 47, 190–201.
Lamrini, B., Lakhal, E., Le Lann, M., Wehenkel, L., 2011. Data validation and missing data reconstruction using self-organizing map for water treatment. Neural Comput. & Applic. 20, 575–588.
Längkvist, M., Karlsson, L., Loutfi, A., 2014. A Review of Unsupervised Feature Learning and Deep Learning for Time-Series Modeling. Pattern Recogn. Lett. 42, 11–24.
Lee, C., Chou, C., Han, C., Huang, R., 2006. Automatic recognition of animal vocalizations using averaged MFCC and linear discriminant analysis. Pattern Recogn. Lett. 27, 93–101.
McCallum, M.L., 2007. Amphibian Decline or Extinction? Current Declines Dwarf Background Extinction Rate. J. Herpetol. 41, 483–491.
Mermelstein, P., 1976. Distance measures for speech recognition, psychological and instrumental. Pattern Recognit. Artif. Intell. 374–388.
Mottaghi-Kashtiban, M., Shayesteh, M.G., 2011. New efficient window function, replacement for the hamming window. Sig. Process. IET 5 (5), 499–505.
Obach, M., Wagner, R., Werner, H., Schmidt, H.H., 2001. Modelling population dynamics of aquatic insects with artificial neural networks. Ecol. Model. 146, 207–217.
Olivier-Maget, N., Hétreux, G., Le Lann, J.M., Le Lann, M.V., 2009. Model-based fault diagnosis for hybrid systems: Application on chemical processes. Comput. Chem. Eng. 33, 1617–1630.

Park, Y.-S., Chon, T.-S., 2007. Biologically-inspired machine learning implemented in ecological informatics. Ecol. Model. 203 (1–2), 1–7.
Park, Y.-S., Cereghino, R., Compin, A., Lek, S., 2003. Applications of artificial neural networks for patterning and predicting aquatic insect species richness in running waters. Ecol. Model. 160, 165–280.
Pettigrew, A., Chung, S., Anson, M., 1978. Neurophysiological basis of directional hearing in amphibian. Nature 272, 138–142.
Piera-Carrete, N., Desroches, P., Aguilar-Martin, J., 1990. Variation Points in Pattern Recognition. Pattern Recogn. Lett. 11, 519–524.
Uribe, C., Isaza, C., Florez-Arango, J., 2011. Qualitative-Fuzzy Decision Support System for Monitoring Patients with Cardiovascular Risk. IEEE- Proceedings of the Eighth International Conference on Fuzzy Systems and Knowledge Discovery, pp. 1621–1625.
Whittaker, K., Koo, M., Wake, D., Vredenburg, V., 2013. Global Declines of Amphibians, Encyclopedia of BiodiversitySecond edition. Elsevier, pp. 691–699.
Wimmer, J., Towsey, M., Roe, P., Williamson, I., 2013. Sampling environmental acoustic recordings to determine bird species richness. Ecol. Appl. 23, 1419–1428.